A Game Theoretic Analysis of Selfish Mobile Computation Offloading

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Mobile Edge Computing (MEC)

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- computing resources and high bandwidth
- low latency
- real-time access to radio network information
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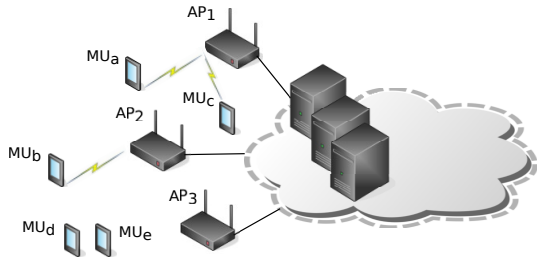

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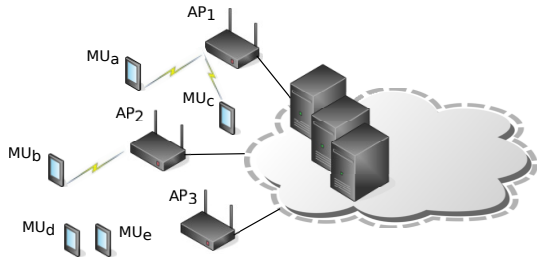
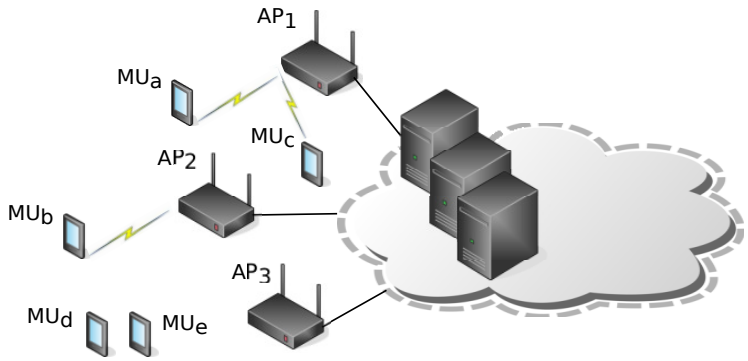


Important question

How to utilize mobile edge resources efficiently?

Mobile Cloud Computing System



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- Set of APs
  $\mathcal{A} = \{1, 2, ..., A\}$
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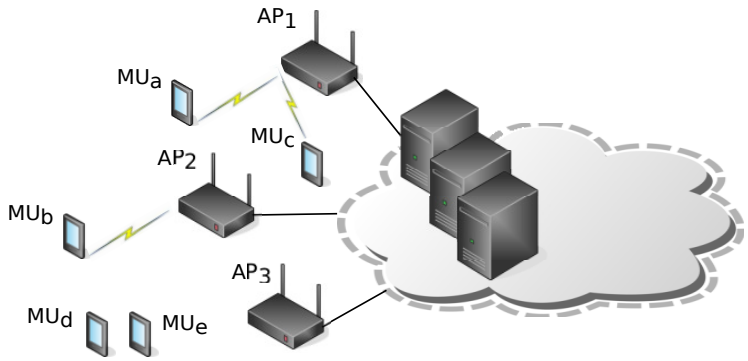

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- Task of MU i, $< D_i, L_i >$
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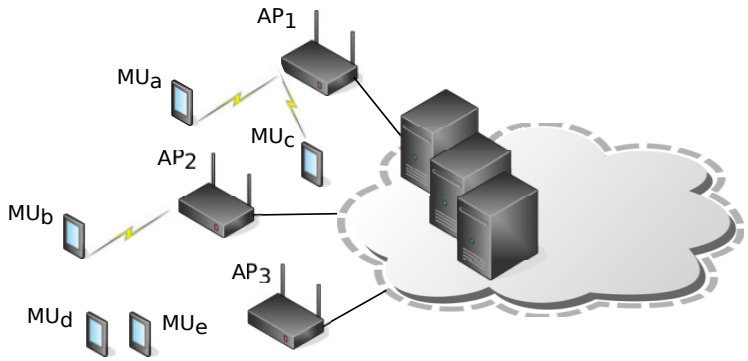

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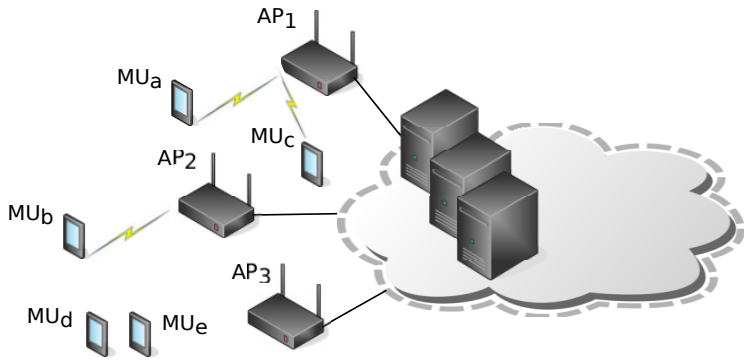

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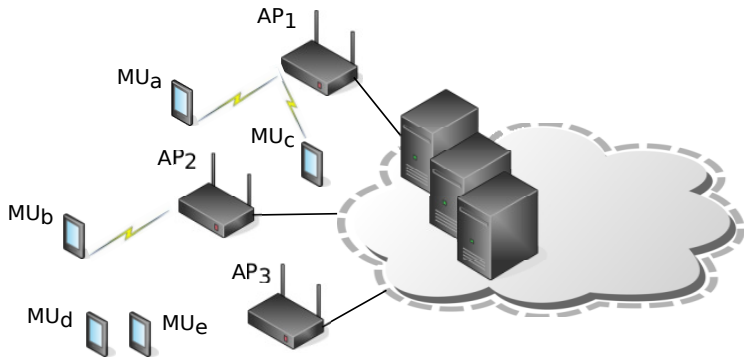

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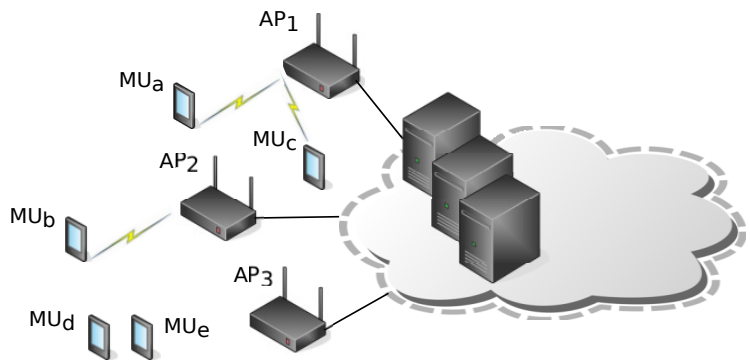

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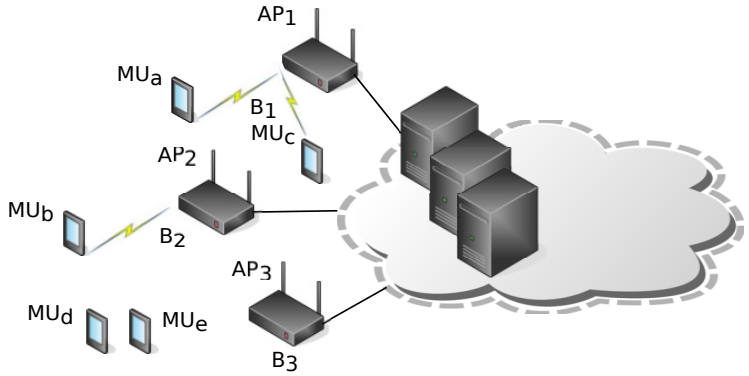
Communication Model



- Uplink rate of MU i via AP a

$$\omega_{i,a}(\mathbf{d}) = \frac{R_{i,a}}{n_a(\mathbf{d})}$$

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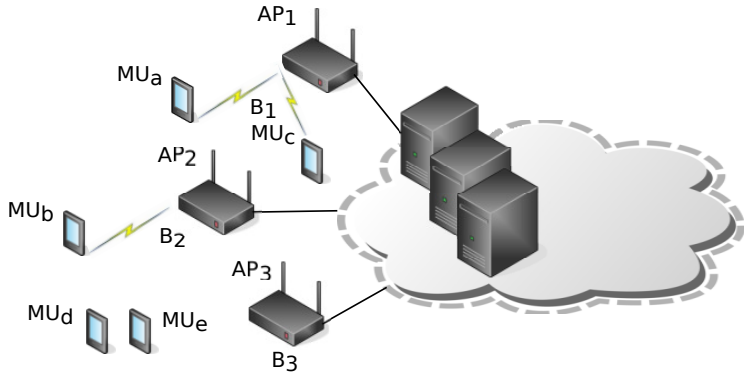

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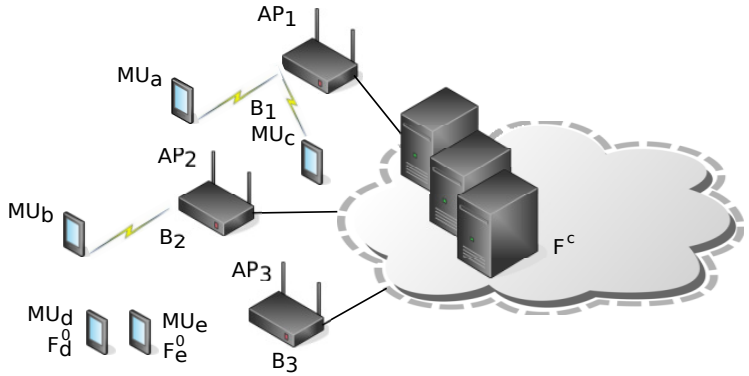
- Transmission time of MU i for offloading via AP a

$$T_{i,a}^{c,off}(\mathbf{d}) = \frac{D_i}{\omega_{i,a}(\mathbf{d})}$$

- Energy consumption of MU i for offloading via AP a

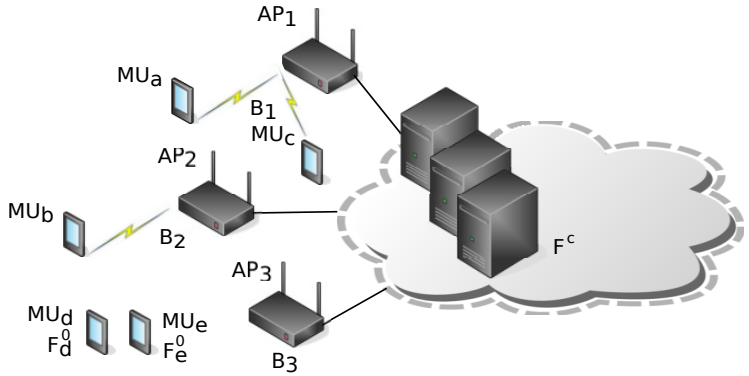
$$E_{i,a}^{c}(\mathbf{d}) = \frac{D_i P_i}{\omega_{i,a}(\mathbf{d})}$$

Computation Model



- Local Computing
  - F_i^0 is the computation capability of MU i
  - Execution time of the task
$$T_i^0 = \frac{L_i}{F_i^0}$$
  - Energy consumption
$$E_i^0 = v_i L_i$$

Computation Model



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- Cloud Offloading
  - F^c is the computation capability of a cloud
  - MU i receives $F_i^c(n(\mathbf{d}))$ amount of computing power
  - Execution time of the task
$$T_i^{c,exe}(\mathbf{d}) = \frac{L_i}{F_i^c(n(\mathbf{d}))}$$

Cloud Model

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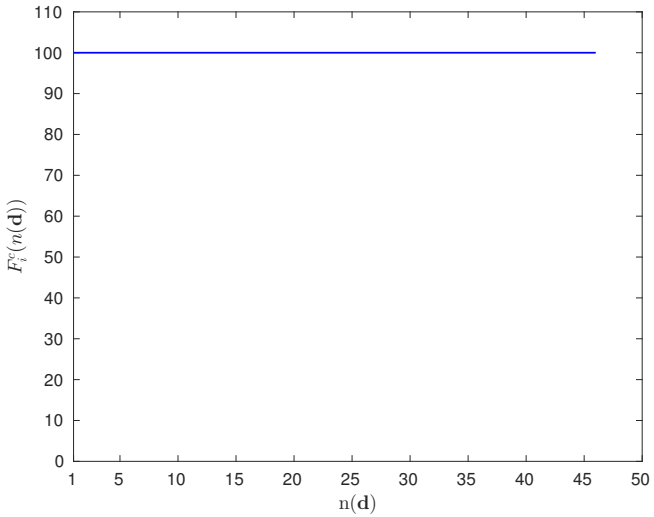
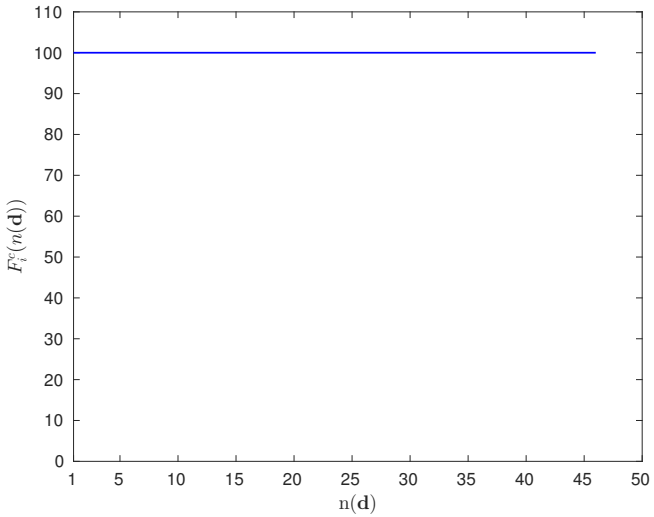


- Elastic cloud
  - $F_i^c(n(\mathbf{d}))$ - constant and equal to F^c

Cloud Model



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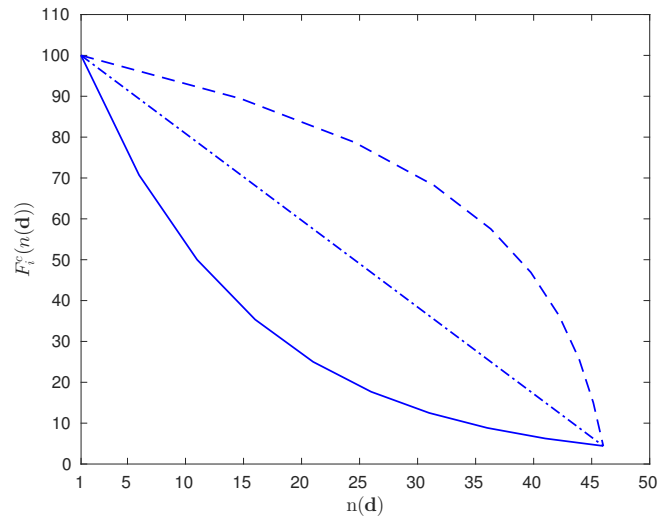

- Non-elastic cloud
  - $F_i^c(n(\mathbf{d}))$ - decreasing function of $n(\mathbf{d})$

Local Computing Cost

$$C_i^0 = \gamma_i^T \underbrace{T_i^0}_{\text{delay}} + \gamma_i^E \underbrace{E_i^0}_{\text{energy}}$$

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Joint computing and radio resource allocation problem

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Joint computing and radio resource allocation problem

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- What is the complexity of the algorithm?
- How good are the system performance?

Computation Offloading Game

Interactions between MUs modeled as a strategic game $<\mathcal{N}, (\mathfrak{D}_i)_i, (C_i)_i>$

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Nash Equilibrium

- Strategy profile d^* in which every player's strategy is a best reply to the other players' strategies
  - $C_i(d_i^*, d_{-i}^*) \leq C_i(d_i, d_{-i}^*)\ \forall d_i \in \mathfrak{D}_i, \forall i \in \mathcal{N}$

Elastic cloud

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NE exists in the case of an elastic cloud

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Sketch of Proof

The computation offloading game with elastic cloud admits the generalized ordinal potential function

$$\Phi(\mathbf{d}) = \sum_{a=1}^{A} \sum_{n=1}^{n_a(\mathbf{d})} log(n) - \sum_{a=1}^{A} \sum_{i=1}^{N} log(M_i R_{i,a}) I(d_i, a),$$

$$M_i = \frac{\gamma_i^E v_i + \gamma_i^T (1/F_i^0 - 1/F^c)}{\gamma_i^T + \gamma_i^E P_i} \cdot \frac{L_i}{D_i}$$

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- Starts from an arbitrary initial strategy profile
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Result

- ImprovementPath algorithm terminates in a NE after a finite number of steps in the case of an elastic cloud

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ImprovementPath algorithm may cycle in the case of a non-elastic cloud

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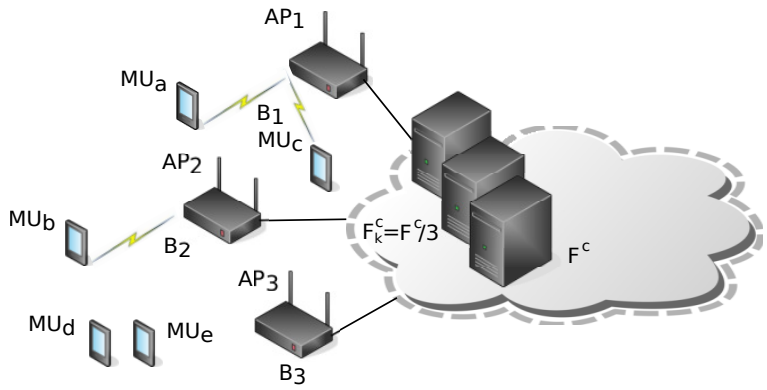

$$(1,2,1,0,0) \underset{c}{\rightarrow} (1,2,2,0,0) \underset{b}{\rightarrow} (1,0,2,0,0) \underset{d}{\rightarrow} (1,0,2,2,0) \underset{e}{\rightarrow} (1,0,2,2,2)$$
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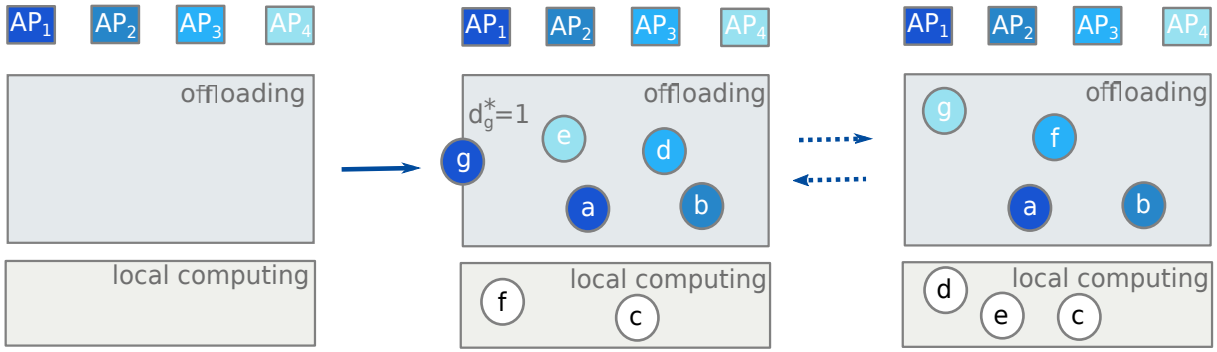
Join and Play Best Reply (JP-BR) algorithm

- Starts from an empty system
- MUs join a system one at a time and play a best reply
- MUs can perform best improvements one at a time



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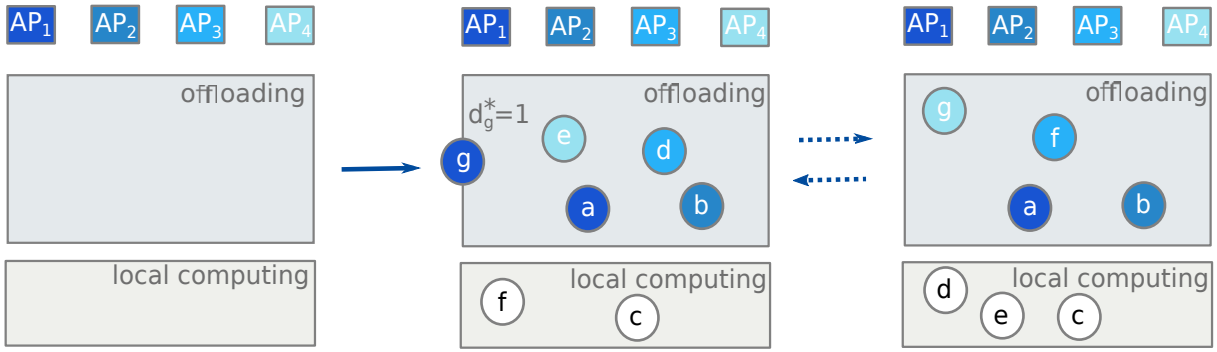

Results

- JP-BR algorithm terminates in a NE both in the case of elastic and in the case of non-elastic cloud
- Computational complexity of the JP-BR algorithm $\sim O(AN^2)$

Price of Anarchy (PoA)

- Ratio of the worst case NE cost and the minimal cost

$$PoA = \frac{\max\limits_{\mathbf{d}^*} \sum_{i \in \mathcal{N}} C_i(\mathbf{d}^*)}{\min\limits_{\mathbf{d} \in \mathfrak{D}} \sum_{i \in \mathcal{N}} C_i(\mathbf{d})}$$

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- Upper bound on the PoA for the computation offloading game:

$$PoA \leq \frac{\sum_{i \in \mathcal{N}} C_i^0}{\sum_{i \in \mathcal{N}} \min\{C_i^0, C_{i,1}^{\bar{c}}, ..., C_{i,A}^{\bar{c}}\}}$$

  - $C_{i,a}^{\bar{c}}$ is the offloading cost of MU i via AP a when she offloads alone

Equilibrium Solution vs. Optimal Solution

Evaluation scenario

- MUs are placed at random over a square area of $1km \times 1km$
- $F^c = 100$ *Gcycles*, non-elastic cloud: $F_i^c(n(\mathbf{d})) = \frac{F^c}{pn(\mathbf{d})}$, $F_i^0 \sim \mathcal{U}(0.5, 1)$ *Gcycles*
- Input data size of the task $\sim \mathcal{U}(0.42, 2)$ Mb
- Complexity of the task $\sim \mathcal{U}(0.1, 0.8)$ *Gigacycles*

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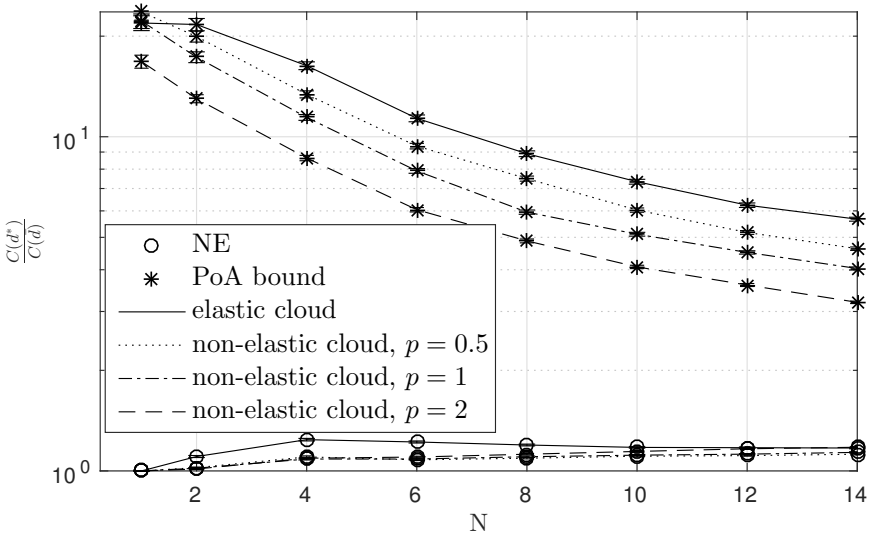

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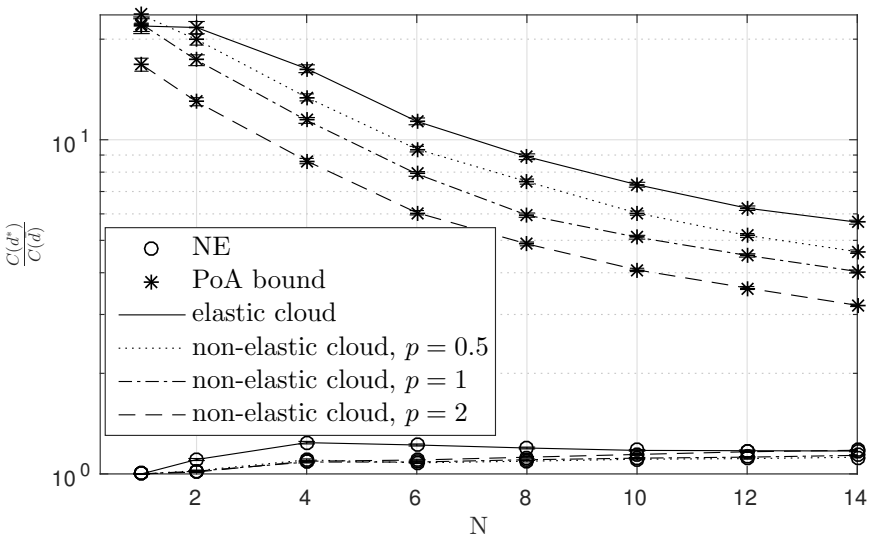

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- Cost ratio is fairly insensitive to the number of MUs

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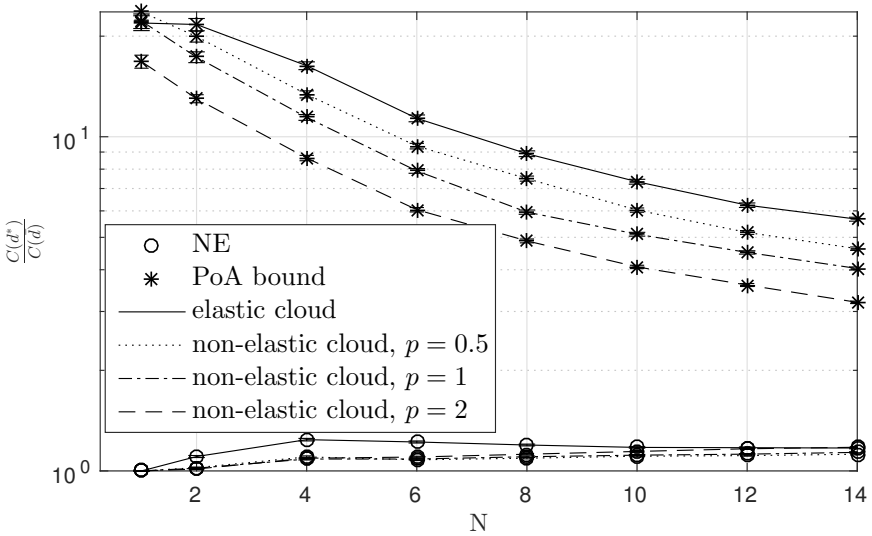

- Equilibrium cost is close to the optimal cost
- Cost ratio is fairly insensitive to the number of MUs
- Upper bound on the PoA decreases as the cloud provisioning coefficient p increases and as the number of MUs increases

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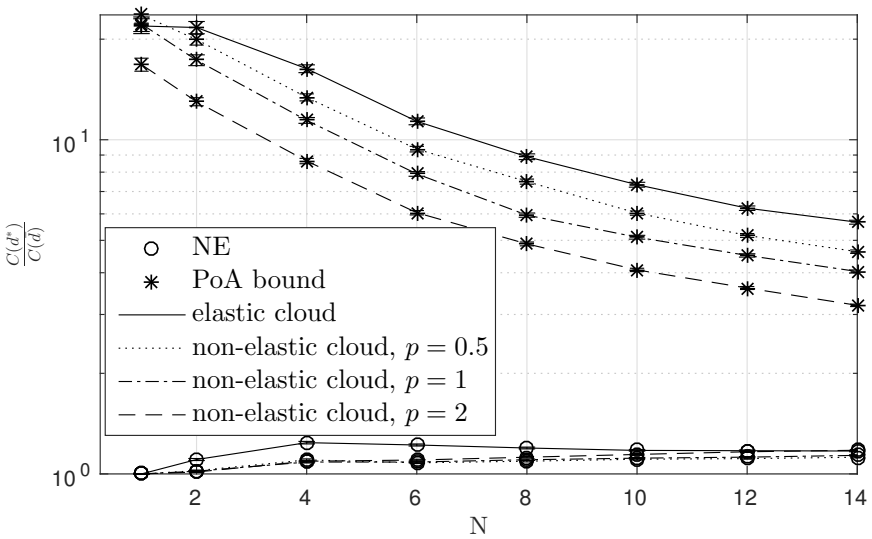

- Equilibrium cost is close to the optimal cost
- Cost ratio is fairly insensitive to the number of MUs
- Upper bound on the PoA decreases as the cloud provisioning coefficient p increases and as the number of MUs increases

Impact of the input data size

Evaluation scenario

- MUs are placed at random over a square area of $1km \times 1km$
- $F^c = 100$ *Gcycles*, non-elastic cloud: $F_i^c(n(\mathbf{d})) = \frac{F^c}{n(\mathbf{d})}$, $F_i^0 \sim \mathcal{U}(0.5, 1)$ *Gcycles*
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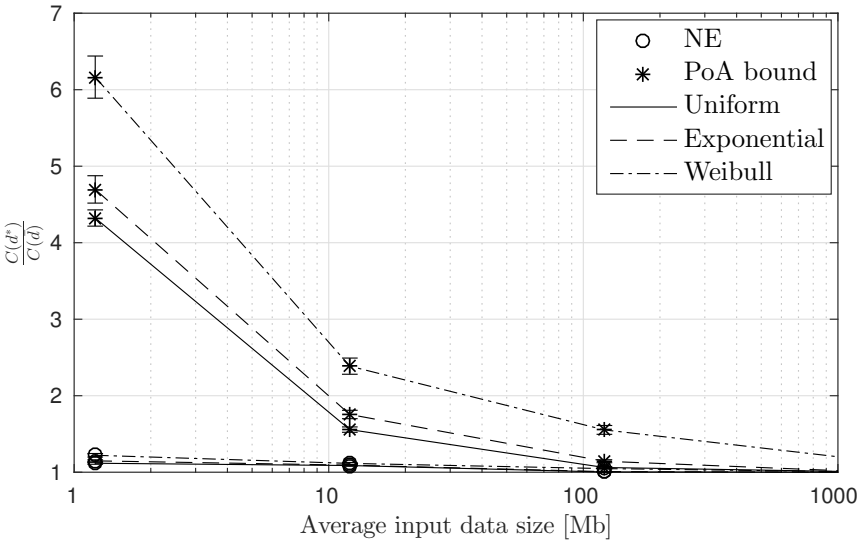

- Cost ratio is fairly insensitive to the mean input data size

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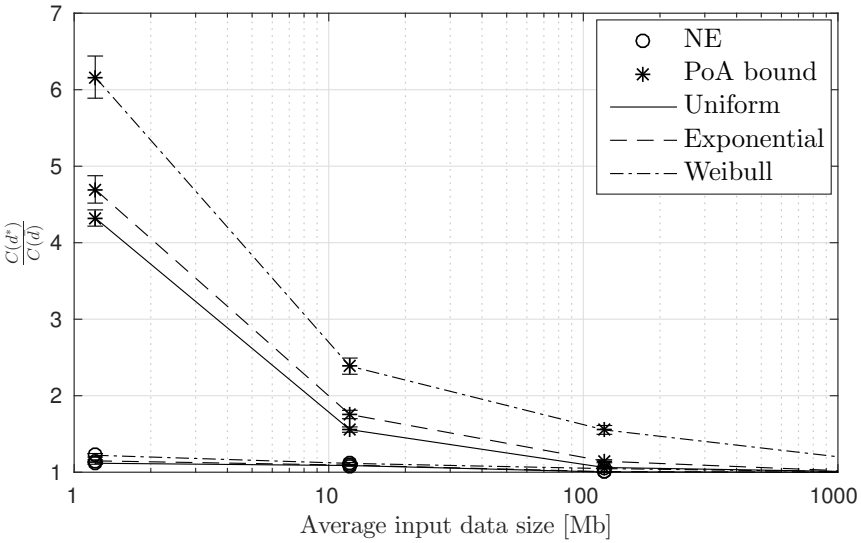

- Cost ratio is fairly insensitive to the mean input data size
- Upper bound on the PoA decreases with the mean input data size and for large data sizes it reaches the cost ratio

Computational complexity

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JPBR algorithm - two orderings of adding MUs (10 APs and 100 APs)

- Random order
- LRF order - MUs are added in increasing order of their ratio $D_i/(C_i^0 L_i)$

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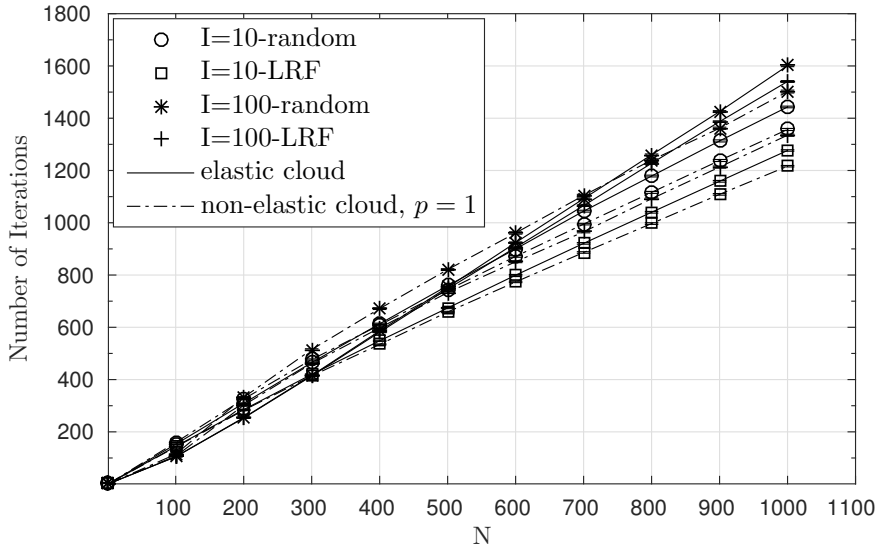

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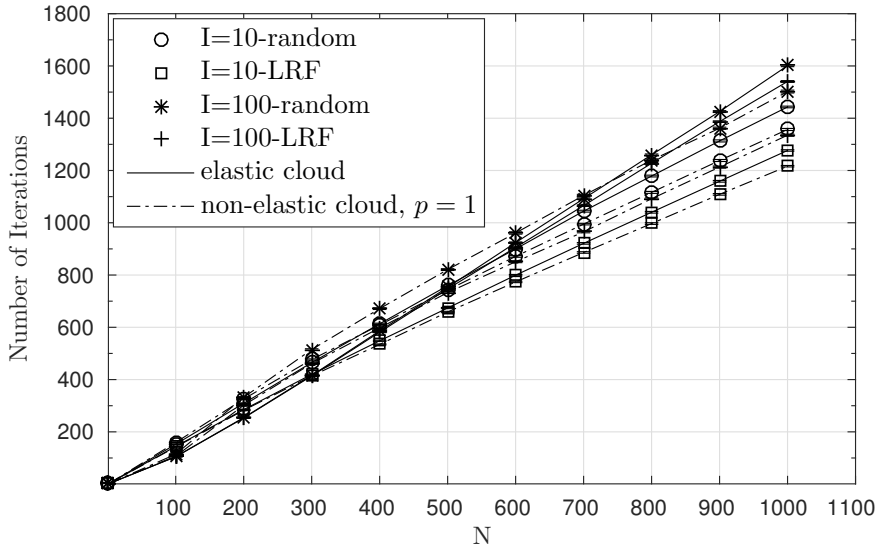

- Number of iterations is fairly insensitive to the order of adding the MUs
- Number of iterations mostly depends on the number of MUs

Summary and Future Work

- Proposed decentralized algorithms for computing an efficient task allocation among selfish MUs
  - elastic cloud
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  - elastic cloud
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- Interesting extensions
  - D2D collaborative computation offloading
  - unknown number of MUs that offload
  - stochastic model of task arrivals

A Game Theoretic Analysis of Selfish Mobile Computation Offloading

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Atlanta, May 4, 2017